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Keywords

spatial learning, spatial location, place learning, place recognition, navigation, hippocampus, evolutionary algorithms, neural networks

Disciplines

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Spatial Learning for Robot Localization

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Abstract

Although *evolutionary algorithms* have been employed to automatically synthesize control and behavior programs for robots and even design the physical structures of the robots, it is impossible for evolution to anticipate the detailed structure of specific environments that the robot might have to deal with. Robots must thus possess mechanisms to learn and adapt to the environments they encounter. One such mechanism that is of importance to *mobile robots* is that of *spatial learning*, i.e., the ability to learn the spatial locations of objects and places in the environment, which would allow them to successfully explore and navigate in *a-priori* unknown environments. This paper proposes a computational model for the acquisition and use of spatial information that is inspired by the role of the *hippocampal formation* in animal spatial learning and navigation.

1 Introduction

Mobile robotics has progressed significantly in the last four decades leading to numerous applications in mail-delivery, material handling and transportation, underwater exploration, autonomous land vehicles, robotic security guards, interplanetary explorers, etc. However, designing mobile robots for specific tasks is not an easy enterprise. Not only must the *physical design* of the robot be developed, but also the *control program* that will make the robot perform the task in question. Both these issues are not easy to address in practice. Evolutionary algorithms [Goldberg, 1989] have proved to be versatile tools for efficiently searching the space of designs, and have been used to discover effective and novel control programs and useful physical robot designs (e.g. sensor placements, robot body plans, etc.). However, despite these advances, the unpredictability and uncertainty of the real-world, and the imprecision and operational noise inherent in the various

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robotic components, collude to render such armchair solutions highly ineffective in real-world settings. Robots must thus be equipped with a suitable set of learning and adaptation mechanisms that will allow them to adapt to the environments in question, and to operate reliably in dynamic, and even novel environments.

Since mobile robots inhabit spatial environments and navigate (and/or manipulate objects) in space, they need mechanisms to identify, remember, and possibly revisit places or objects of particular import. Such mechanisms for representing spatial information can be of great value in the attainment of their goals, like avoiding obstacles, transporting specific objects from source to destination locations, approaching reward sites and steering clear of dangerous locations, etc. If the robot always operates in *a-priori* known environments, such spatial information can be provided by the user. However, if the robot is to operate in *a-priori* unknown environments or in an autonomous fashion, it must have the ability to acquire such spatial information on its own, a property we term *spatial learning*. Spatial learning has two important components: *place learning (PL)*, which refers to the process of acquiring and remembering different places based on some set of distinguishing attributes, and *place recognition (PR)*, which is the process of recognizing the current place by matching its attributes with the ones stored in memory.

In mobile robotics, the issue of spatial learning has received much attention. Many of the approaches use variants of a *topological map* to represent spatial information. A topological map is a directed graph of nodes and arcs, with the nodes representing *distinctive* places and the arcs representing the robot motions required to get from one distinctive place to the other [Brooks, 1985]. The primary advantage of such maps is their compact representation of space (as only distinctive places are represented and not the entire world), and their resistance to the accumulation of global movement errors (since the robots only navigate locally between places). Many variations of such topological maps exist depending on how distinctive places are represented: sonar signatures [Kuipers & Byun, 1991, Mataric, 1992], visual signatures [Engelson, 1994, Taylor & Kriegman, 1995], combination of sonar and vision [Kortenkamp & Weymouth, 1994], dead-reckoning estimates [Yamauchi & Beer, 1996], etc. The primary problem with such representations is that robot navigation becomes restricted to a form of *route following*, with the robot following a path in the topological map, from a node corresponding to the current position to a node corresponding to the target location. Thus, without any *metric* information, the robot cannot take *short-cuts* to goals.

Other approaches to spatial map learning have used *occupancy grids* [Moravec & Elfes, 1985] or *adaptive Kalman filtering* techniques [Hebert *et al.*, 1995] to allow the robot to incrementally build and maintain a representation of the environment. Importantly, these approaches provide effective ways of dealing with uncertainties in the information from the various low-precision sensors. Once such a spatial map is learnt, current perceptual inputs are matched against the map in order to determine the current position of the robot. As exact matches between the perceived and stored objects are unlikely, some form of approximate matching must be performed. Assuming normally distributed errors, Kalman filtering techniques can be used to correct odometric (or position estimation) errors based on perceptual inputs [Crowley, 1995]. Other such approaches include the *fuzzy localization algorithm* [Saffiotti & Wesley, 1995] and the use of a *hill-climbing* process to match evidence grids [Yamauchi & Beer, 1996].

On the other hand, animals demonstrate exceptional abilities for acquiring and responding to spatial information, including highly sophisticated spatial navigation behaviors. For instance, ants, bees, rodents, doves, etc., demonstrate a suprising sense of space, and are capable of navigating to their homes even after pseudo-random movements in search of food or their young [Gallistel, 1990]. How do these animals perform spatial learning? Presumably evolution provides them with the necessary apparatus and appropriate neural structures, but how do these structures get adapted to facilitate spatial learning? It would be a rewarding exercise to explore the nature of spatial learning in such biological forms, particularly because it might suggest new possibilities for spatial learning in robots.

Based on the data regarding biological spatial learning, we have formulated a spatial learning model for mobile robots. Essentially, distinctive places and objects of import are represented in terms of both, their physical attributes as well as their estimated position in a metric framework computed by the robot. In order for the metric framework to be consistent, and devoid of errors, we suggest that a module like the hippocampus acquires spatial relationships present in the environment, thereby correcting errors in position estimates.

In this paper, we present the motivations for the spatial learning model, and describe the robot spatial learning model in detail. We also present some experimental results on the ability of the robot to localize using this model. Finally, we suggest possibilities for using this spatial learning model within an evolutionary framework.

2 Animal Spatial Learning

For most animals, locomotion (and hence navigation) of some form is an essential part of its behavioral repertoire, which is required to find food, avoid predators, find mates, etc. Animals appear to perform this task seemingly effortlessly, and in many cases, with a great deal of enterprise. Many behavioral experiments have been performed to help identify the nature of the processes of spatial learning in animals, and how they acquire and store spatial properties of their environments. Such experiments have led to the following insights:

1. *Dead-reckoning* plays an important role in animal navigation. The term is thought to be a corruption of *deduced reckoning*, and refers to the process of updating one's estimate of one's position on the basis of knowledge of how fast one has been moving, in what direction, and for how long. There is considerable evidence that dead-reckoning is used by animals to maintain an estimate of their current position from some suitable origin of measurement [Gallistel, 1990, Mittelstaedt & Mittelstaedt, 1982]. However, without frequent calibrations based on visual inputs, such dead-reckoning systems rapidly accumulate errors [Etienne, 1992, Etienne *et al.*, 1996].
2. Based on experiments in the water-maze task (where a rat is released into a pool of opaque water and has to swim to a submerged, hence hidden, platform), researchers have concluded that rats compute and store *vectors* to landmarks visible from the hidden platform. Thereafter, when released in the pool, they are able to compute a direct vector to the position of the submerged platform by subtracting the stored vectors to landmarks from the goal and the vectors to the same landmarks from the current position [Morris, 1981, Keith & McVety, 1988]. Experiments with gerbils have led Collett *et al.* [1986] to conclude that goal locations are remembered as an *independent set of vectors* to *individual* landmarks visible from the goal. Further, when reintroduced into familiar environments, the gerbils showed themselves capable of *reorienting* in the environment by matching stored spatial attributes of the environment with currently perceived ones. By manipulating the attributes of the environment, Collett *et al.* concluded that the gerbils appear to use *relationships between* landmarks to reorient rather than single landmarks, a conclusion that was also reached by Biegler and Morris [1996]. For more details regarding these and other experiments, the reader is referred to [Balakrishnan & Honavar, 1997a].

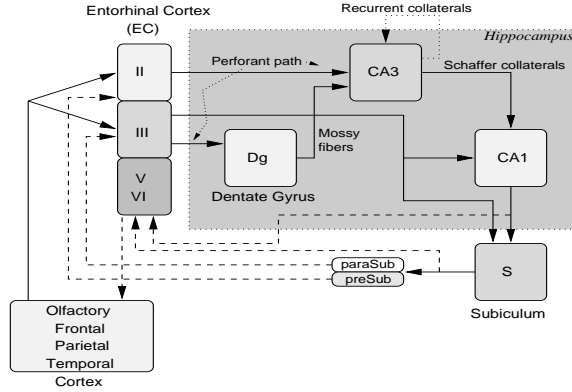


Figure 1: A model of the hippocampal formation.

In the neuroscience community, the hippocampal formation and adjacent cortical regions of the medial temporal lobe have long been associated with spatial learning and memory, primarily through data that hippocampal lesions impair spatial learning skills in humans and animals [Churchland & Sejnowski, 1992, Cohen & Eichenbaum, 1993]. As shown in Figure 1, the hippocampus receives highly processed sensory inputs from higher-order associational areas of the cerebral cortex, which converge primarily in the *entorhinal cortex*. These inputs could perhaps be *recognized* objects (from the neocortex) and their *estimated* spatial positions (from the parietal cortex). The hippocampal formation itself consists of the *dentate gyrus* and the areas *CA3* and *CA1* of Ammon’s horn. The hippocampal formation outputs to the *subiculum*, which in turn projects both to the *pre-* and *para-subiculum* and to the deep layers of the entorhinal cortex. For details regarding hippocampal function, the reader is referred to [Churchland & Sejnowski, 1992].

Apart from lesion data, cellular recordings of hippocampal cells have served to identify some crucial properties of signal processing in the hippocampus:

1. Pyramidal cells in the regions CA1 and CA3 of the rat hippocampus appear to fire only when the rat is in a particular portion of its environment [O’Keefe & Dostrovsky, 1971]. For this reason, the pyramidal cells have been termed *place cells* and the region over which they fire, their *place field* [O’Keefe & Nadel, 1978]. Recent work by Wilson and McNaughton [1993] has shown that not individual cells, but an ensemble of them code for a region of the environment. However, the exact nature of the code is still open to debate. The place fields appear to shift with manipulations of the environmental cues (or landmarks) suggesting that visual cues are used to initialize the place fields when the animal is reintroduced into

familiar environments [O’Keefe & Speakman, 1987, Muller *et al.*, 1987]. Further, once the place fields are initialized, they persist even after landmarks are removed or lights are switched off, suggesting that place cell firing is maintained by some means other than visual input [O’Keefe & Speakman, 1987, McNaughton *et al.*, 1989, Quirk *et al.*, 1990]. Dead-reckoning is strongly suspected to be involved in the maintenance of place cell firing.

2. *Head-direction cells* have been found in several regions of the brain, including the dorsal pre-subiculum and the posterior parietal cortex [Taube *et al.*, 1990a, Chen *et al.*, 1994]. These cells appear to fire preferentially based on the current orientation of the animal’s head, irrespective of its location in the environment. This endows the animal with a form of *built-in compass*. Head-direction cells also appear to be controlled by visual cues and maintained by dead-reckoning [Taube *et al.*, 1990b, McNaughton *et al.*, 1995, Knierim *et al.*, 1995]. Further, alteration of the reference direction for one such cell changes the reference direction for all the cells by an equivalent amount.
3. The motor system is also strongly linked to the establishment of place fields. For instance, when rats were wrapped in a towel, restraining their motor activity entirely, almost all hippocampal neuronal activity ceased. Neuronal activity did not resume even when the rats were *passively* moved through the environment to regions that resulted in place cell firing earlier [Foster *et al.*, 1989]. Similar results were also observed with head-direction cells [Knierim *et al.*, 1995].
4. Finally, without frequent visual recalibration, the firing of place cells and head-direction cells drift, accumulating considerable errors.

Based on some of this data, many models of the hippocampal formation and its purported role in spatial learning, have been proposed. O’Keefe and Nadel [1978] suggested that animals represent spatial information in the form of *cognitive maps* grounded in motion-related metric information, which are then used for computing short-cut trajectories to goal locations. A number of computational models of visual-input driven place cells have been proposed [Zipser, 1986, Sharp, 1991, Treves *et al.*, 1992, Mataric, 1992, Schmajuk & Blair, 1993, Burgess *et al.*, 1994], which, however, cannot explain the data concerning persistence of place fields after the removal of landmarks or in darkness. On the other hand, the *adaptive place networks* of Yamauchi and Beer [1996] use place

units driven purely by dead-reckoning estimates of the robot and no sensory information.

Recently, Redish and Touretzky [1996] proposed a model that uses ensembles of cells to define places, with each of the cells responding to the visual attributes of one landmark and to the spatial relationship between at most two landmarks. However, they do not use their model for navigation purposes, and hence there is no dead-reckoning error. Further, they assume that the goal location is the origin of the dead-reckoning system, which leads to problems if the animat is to be released into the environment with no knowledge of the goal location and has to explore the environment to find it.

Unlike other models, our model of spatial learning is based on the hypothesis that the hippocampal formation only serves as a system to localize the animal, thereby correcting any drifts its dead-reckoning system might accrue. If the hippocampal system can maintain reliable dead-reckoning estimates, the animal can then represent interesting objects and locations in terms of the dead-reckoning estimate. These locations of interesting objects are stored outside the hippocampal formation, consistent with data from neuroscience. Our model is also consistent with the results of behavioral experiments as well as the data from neuroscience concerning the structure and functioning of the hippocampal formation (that is known to date), and is related to the work of McNaughton et al. [McNaughton *et al.*, 1995, McNaughton *et al.*, 1996]. However, it differs from their work in providing in a concrete implementation of the theory.

3 A Computational Model for Spatial Learning in Robots

As mentioned earlier, our spatial learning model relies on the ability of the robot to perform dead-reckoning, which is a common feature of contemporary real-world robots. The origin of the robot's position estimate is taken to be its start position. Thereafter, with each move and turn, the robot updates its position estimate using dead-reckoning. Of course dead-reckoning is error-prone, but our computational model of the hippocampal formation, corrects these dead-reckoning errors, thereby maintaining reliable and faithful position estimates. We also assume that the robot can estimate the distance and heading of landmarks or other objects that it encounters. Again, real-world robots have access to a wide variety of ranging sensors and compasses that allow the robot to robustly determine the *egocentric* (with respect to the robot) location of landmarks and objects.

Let us assume for the moment that the position estimates are correct. As the robot moves about performing its task, its sensors might detect objects that might be of import, say a power source which the robot might have to visit later in order to charge up. The robot can store the power source (its attributes as well as its estimated location), in its *goal memory*. The location of the power source can be computed based on the robot's current position estimate and the distance and heading of the power source from the robot. Later, if the robot is in need of power, it can refer to its goal memory to identify the position of the power source. Since the object positions are grounded in metric space (e.g. Euclidean), the robot can also determine the location of the *nearest* power source. Further, goal locations may also be remembered in second order forms, i.e., the robot might choose to remember a goal position in terms of distance and headings to landmarks visible from that location. In such cases, in order to locate the goal position, the robot would first need to find the appropriate landmarks.

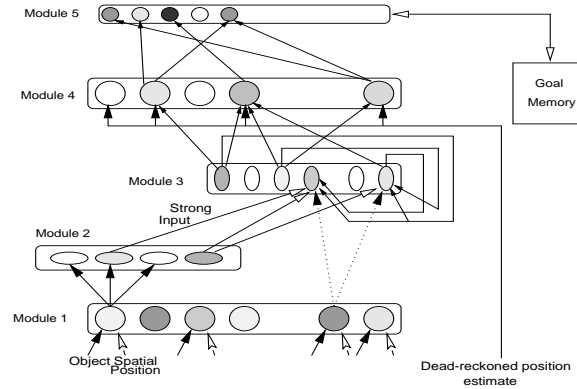


Figure 2: A computational model of the hippocampus.

Having described the overall functioning of the spatial learning system, let us now describe in detail our computational model of the hippocampus that makes all this possible. Paralleling the anatomy of the hippocampal formation, our model too, is composed of five modules as shown in Figure 2. Module 1 receives *highly processed* inputs from the sensory streams, which might correspond to recognized objects at estimated spatial positions. Note that this recognition does not have to be complete; it could have uncertainty associated with it. Units in module 1 fire if particular objects are detected at particular estimated positions. Thus these units can be thought of as *spatial-object filters* that respond either to *egocentric* positions of objects or to their *meta-egocentric* positions. An egocentric unit would fire, say, when the robot detects a wall 2 meters

ahead irrespective of which direction it is facing, while a meta-egocentric unit would fire only when the robot detects a wall 2 meters to, say, its north. Redish and Touretzky [1996] refer to the units of the latter kind as *allocentric*. In our view, allocentric units encode object positions in terms of their *absolute* position in a larger frame of reference, for instance, in a room. Such units have been found in primate hippocampus [Feigenbaum *et al.*, 1987], but are not used in our model at present. In any case, module 1 units respond to combinations of object attributes and their positions.

Modules 2 and 3 both form associations of spatial features detected by module 1. Since module 2 is connected to module 3 through strong links, the feature associations in module 2 can influence the associations formed in module 3. We suspect that stable and reliable features (e.g. distal landmarks) are associated in module 2, and would have overriding privileges over other, less reliable inputs in cases of conflict, as might happen, for instance, when the robot is reorienting itself in the environment. The firing of the units of module 3 represents a *distributed place code* for the current location of the robot in its environment in terms of its perceived sensory features. The units of module 4 simply associate this place code with the robot’s dead-reckoning estimate. Further, module 5 of the model contains head-direction cells, which are associated with the active cells of module 4, allowing head-direction estimates to be initialized or corrected.

At any given position in its environment, the robot processes its sensory inputs to determine detected objects and their estimated positions. Based on these processed inputs, some units in module 1 would fire. These activations are propagated to modules 2 and 3 that fire if sufficiently many of the module 1 units that they are connected to are active, producing the corresponding place code at the outputs of module 3. If this place code represents a new place, the new position estimates are encoded in the set of module 4 units that fire. However, if the place code corresponds to a visited location then the current dead-reckoning estimate can be reinitialized from the ones stored in the module 4 units that are active. Drifts in the head-direction system can be corrected in a similar fashion by module 5. This allows dead-reckoning estimates to be constantly updated and corrected, thereby maintaining reliable and faithful estimates, as was our need. For more details, the reader is referred to [Balakrishnan & Honavar, 1997a].

4 Implementation Details

Our goal was to implement a computational model of the hippocampus that would allow the robot to perform spatial learning to maintain accurate dead-reckoning estimates. The relevant simulation details are as follows. The simulated robot is released into a square room of dimension 10 units, with 10 boxes placed at random locations. The boxes are identical and hence not distinguishable from each other. Similarly, the walls of the room are also not distinguishable. In addition, the room also has two identical power sources. The robot is assumed to have range sensors of maximum range of 5 units that can be used to determine the distance of detected objects. However, the sensed range is not completely accurate, and range error is modeled by adding white Gaussian noise (with variance 0.001 per unit distance), to the actual range. Further, the sensors are assumed to be *ray* like with no beam spread, and operate in a single plane. Hence, closer objects in the path of the sensor ray will occlude objects beyond. In our simulations in this paper, the robot had 12 sensors, placed at 30 degree intervals around it.

When sensors detect objects, their recognition is not complete. We have used a model in which the confidence (or certainty) of recognizing a particular object is proportional to the angle of incidence of the range sensor ray on the face of the detected object. Thus, encountered objects are recognized with certainties of $[0,1]$, with higher certainties if the sensor ray is perpendicular to a face of the object. Since the robot environment only contains three kinds of objects: walls, boxes, and power sources, the internal representation of a sensor's input is a 3-tuple, denoting the certainties of the sensed object being a wall, box, or a power source. We also prescribe that a certainty value greater than 0.5 *suffices* to recognize objects completely.

The robot randomly explores the environment through forward moves and left or right turns of 90 degrees. The turns are in-place, while a forward move advances the robot by 1 unit unless the robot is against some obstacle (wall, box, or power source). As the robot moves, it maintains a dead-reckoning estimate of its current position. Dead-reckoning error manifests itself in the form of an additive white Gaussian with variance of 0.01. Thus, although the robot is at some position, it *thinks* it is somewhere else. It is these errors that the robot must learn to correct.

Our model of spatial learning is a simplification of the model presented in the previous section. In effect, this model only realizes modules 1 and 4 discussed above. In this simplistic version, units of module 1 use Gaussian tuning curves with means at stored values and variances of 0.1

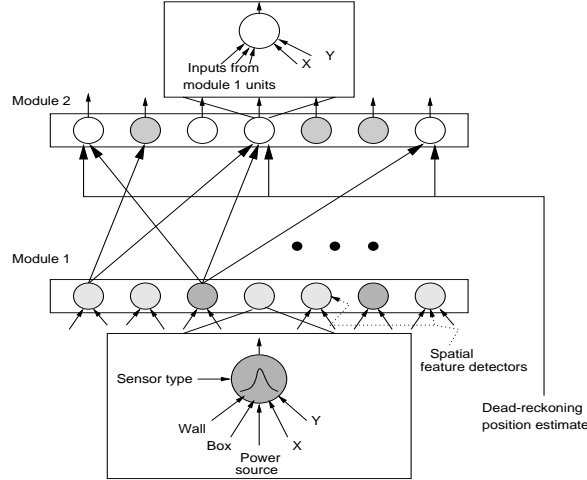


Figure 3: Simplified model implemented in this paper.

for each of their input parameters (certainties of wall, box, and power source, and the position coordinates of the object in a Cartesian system). These units could be of two types: egocentric and meta-egocentric, as mentioned in the previous section. The net output of each unit is a simple product of the Gaussians for each of its input parameters, as shown in Figure 3.

The network of units is built as the robot explores its environment. If a sensor detects an object (i.e., certainty value ≥ 0.5), then the activations of the first module are checked to see if units exist that produce responses greater than an *activation threshold* for both egocentric as well as meta-egocentric positions of the detected object. If one or both kinds of units are not found, new ones are *inducted* and initialized to the currently detected object and its appropriate position. Once the input activation is faithful, i.e., all detected objects activate at least one egocentric and one meta-egocentric unit in the first module, activations of the second module are calculated. The units of this module represent particular combinations of spatial features detected by module 1. Here again, if no unit is found that represents the combination of *all* the currently active units of module 1, a new unit is inducted and is connected to the active units of module 1. Each such newly inducted unit is also associated with the current dead-reckoning estimate. If however, the input activations sufficiently excite a unit of module 2, then the current position estimate is reinitialized from the estimates stored along with the active unit.

We tested the effectiveness of this spatial learning system in correcting dead-reckoning drifts, by placing the robot at a random location and allowing it to move randomly for a given amount of time. At the end of the simulation, we computed the *distance* between the robot's actual position

in the environment and its dead-reckoned position. We also compared the dead reckoned position with and without the use of the spatial learning module. The results are averaged over 5000 random environments, and are presented in Table 1.

Table 1: Simulation results

Sim time	Drift with learning	Drift w/o learning	Units in module 1	Units in module 2
200	0.6497	1.5508	206.60	109.61
500	0.7624	2.4701	262.44	249.75

As can be observed, spatial learning helps keep the dead-reckoning estimate very close to the actual position of the robot. Further, with increased simulation time, dead-reckoning errors become more rampant, but the spatial learning system is still able to maintain reasonably correct estimates. The number of units inducted by the algorithm depends on the simulation time since with more time at its disposal the robot explores more of its environment, and hence more *places* have to be remembered. In our experiments, we found that there were runs in which the error with spatial learning was more than without spatial learning. This happens because those environments present the robot with the same perceptual inputs at many different locations, misleading the dead-reckoning correction procedure. However, this happens in fewer than 9% of the presented environments. Also, with increased probability of error of dead-reckoning, the usefulness of the spatial learning and localization process becomes even more apparent. For instance, when dead reckoning errors are increased to additive white Gaussians with variance of 0.1, the average drift with learning is 2.02 while the drift without spatial learning is 4.94 (for a simulation time of 200).

5 Summary and Discussion

Evolutionary algorithms are versatile tools for searching large design spaces with little *a-priori* domain-specific knowledge. They have thus found use in evolutionary robotics in the design of behavior and control programs for robots, and in some cases, even in the design of robot *body-plans* [Lund *et al.*, 1997]. In our past work we have used evolution to design neural network controllers for a simulated robot under a variety of environmental constraints. The robot had the task of clearing a square room (much like the environment used in this paper) by push-

ing the boxes to the walls. Evolution found efficient, appealing, and often novel controllers for the robots [Balakrishnan & Honavar, 1996a]. We also used evolution to determine effective placements of the sensors and their ranges, while also evolving designs robust to sensor faults [Balakrishnan & Honavar, 1996b, Balakrishnan & Honavar, 1996c].

Consider a related, but more difficult problem. Suppose the robot only has a limited battery capacity. Now, as it performs its box-pushing task, it will lose energy due to the operation of its sensors, neurocontroller units, its motors, etc. Thus, the robot might be required to approach a charging station (power source) and charge up. To make things difficult, let us assume that the positions of the power sources vary in each trial. Thus, evolution would have little luck in building mechanisms for the robot to charge up as it cannot anticipate the positions of the power sources in each of the robot’s environments. The robot thus needs a mechanism for *learning* the locations of the encountered power sources, making it possible for it to navigate to them when in need. In general, the robot might need to learn the locations of many different kinds of objects and places in order to fulfil its task, thereby requiring robust spatial learning mechanisms. In some preliminary work, we used evolution to evolve the control program for the box-pushing robot, where the robot had limited battery power. Thus, the robot had to detect and remember the locations of power sources in the environment, and approach them when in need of power. We used a simplified model of spatial learning (in effect, just module 1 of the model in this paper), to remember the locations of power sources encountered by the robot in the course of its box-pushing task. With the spatial learning module built-in, evolution discovered high fitness designs with compact neurocontrollers and few sensors in key positions [Balakrishnan & Honavar, 1997b]. However, in this experiment, there were no errors either in sensing or in the robot’s actions.

In this paper we have proposed a model of spatial learning for robots that is capable of handling errors both in sensing as well as in actions. This model is strongly inspired by neurobiological and cognitive psychology literature, and consists of labeling the positions of interesting objects and places by position estimates based on dead-reckoning, and range and heading information from sensors and compasses. The crucial part of the system is a simplified, computational model of the hippocampal system, which builds spatial relationships between encountered objects, thereby allowing for *moment-to-moment* correction of dead-reckoning estimates. We have realized a simplified version of our model and used it in a simulated environment, albeit with reasonably realistic sensing and action models. Our results indicate that the robot localizes extremely well in the envi-

ronments it encounters, with very little dead-reckoning drift. Further, the algorithm automatically inducts units on an as-needed basis to construct the eventual network needed for the particular environment.

The spatial learning mechanism described in this paper is quite powerful. Unlike other approaches in the literature, our model *does not* require the landmarks to be *distinguishable* from each other. In fact, our simulations created environments containing many identical objects. This does not pose any problems for our model, since it remembers places based on *spatial relationships* between landmarks sensed from the given position, and not based on individual landmarks. Indeed, it can be argued that if the environment guarantees that no two locations will have an identical set of sensory inputs, then this algorithm will localize extremely reliably. We observed this in our experiments. Importantly, this requirement is far less severe than the need for each of the landmarks to be distinguishable.

The model described in this paper can also be used to handle *dynamic environments* in which objects move. As the hippocampal input is the result of highly processed sensory inputs, one would suspect that the moving objects will be spatio-temporally integrated and would not even be provided as input to the hippocampus. There is some evidence from animal behavior studies that suggests that moving objects are not used for spatial localization [Bennett, 1993, Biegler & Morris, 1996]. On the other hand, if some objects happen to move after the robot has registered them in the spatial system, subsequent visits to that position would pose problems for the system implemented in this paper. However, if modules 2 and 3 are also implemented, place localization could take place, yet, the weights on the links between module 1 and modules 2 and 3 could be adapted to reflect the absence of the object at the given location.

The model implemented in this paper is only the first step. Our goal is to have a complete localization system based on the discussion of Section 3. We are in the process of formalizing the update rules and learning mechanisms for modules 2 and 3. The current model does not correct for head-direction drifts. Implementing module 5 would allow the system to do that as well.

It might be possible to use evolution to determine the broad specifications of the spatial learning system. For instance, the number and activation properties of units in each of the modules, the learning and adaptation mechanisms operating between units in different modules, etc., could be evolved. Further, the spatial learning system derives highly processed sensory inputs from the sensors. The nature of sensory processing required to convert raw sensory data into a form suitable

for input to the spatial system, could also be determined by evolution.

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